A System Approach to Machinery Condition Monitoring and Diagnostic

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I. ABSTRACT

The purpose of this paper is to discuss an approach to integrate data collection and analysis of ship machinery for the purpose of assessing equipment condition and maintaining their operational performance. The approach exploits the capability of Distributed Control Systems (DCS) in a networked environment to support a system-wide condition based maintenance (CBM) concept in a cost effective way. The paper first discusses the CBM concept in a distributed computing environment for shipboard application. It then proceeds to discuss the traditional roles of distributed control systems for shipboard equipment and expounds on different features of the advanced DCS that enable it to monitor and assess equipment condition on-line and continuously to predict/prevent performance degradation. Some of the new features that are integral to the control system include advanced vibration analysis algorithms and system dynamics identification techniques whose purpose is to assess the performance of the equipment based on the measured dynamic response. This monitoring and assessment capability adds to the CBM suites of assessment and prognostics techniques, but at no additional costs, since the DCS already handles the collecting and conditioning of the equipment critical data.

II. INTRODUCTION

Typical shipboard machinery includes turbines, engines, motors, expanders, pumps, compressors, and generators plus various integral components (valves, piping, etc.) that make up each individual system. The basic notion of equipment maintenance is about applying engineering principles toward the diagnosis and correction of machinery malfunctions. The development of CBM methodologies coupled with advanced distributed computing technology have facilitated the utilization and implementation of engineering principles and experience into a ship-wide automated maintenance strategy. In modern machinery plants, the distributed process control system has taken over the data collection and analysis tasks that have traditionally been performed in dedicated machinery monitoring systems. The general trend is to incorporate monitoring functions and assessment algorithms into the equipment control systems located throughout the plant. This approach tends to reduce data acquisition costs and improve operating efficiency since the control systems already collect signals that are critical for diagnosing and predicting machinery condition and performance.

Distributed control systems for individual equipment play a critical role in the intermediate step of data collection, conditioning, and analysis within the automated CBM infrastructure. Advanced process control systems include analysis algorithms that enable them to diagnose and report malfunctions to the CBM system which ultimately supports system-wide asset management. Figure 1 depicts the distributed architecture applicable to ship machinery condition diagnostics and prognostics. A typical distributed control system operates at the component or equipment level where data from equipment sensors are collected, conditioned, and analyzed for machinery behavior. Depending on the maintenance philosophy and on the interaction among ship equipment, further diagnosis and prognostics may take place at higher level in the architecture, i.e. zonal, system, or ship-wide.

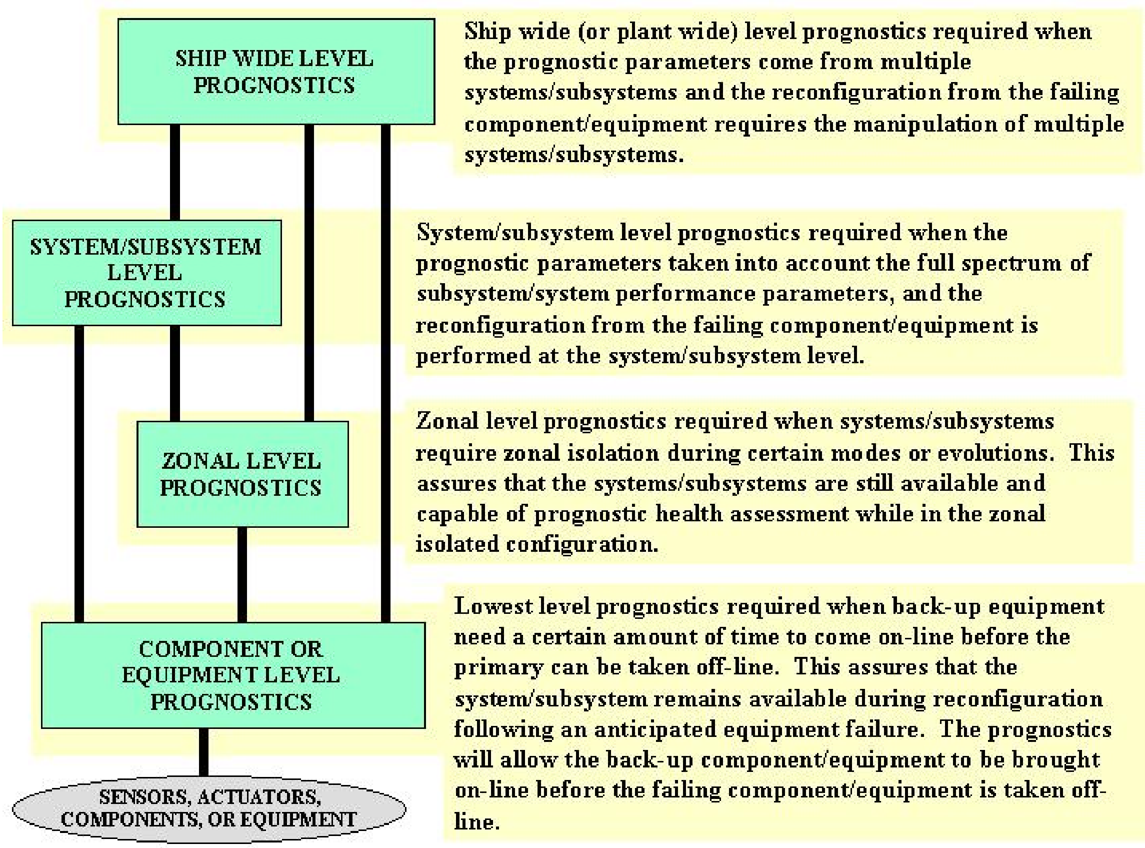

Figure 1: Ship Equipment Maintenance Hierarchical Architecture

III. Condition Based Maintenance (CBM) Concept

Condition Based Maintenance (CBM) functionality can be viewed as a tightly integrated suite of software applications operating throughout the ship distributed computing infrastructure. It integrates sensors, algorithms, and software, and supports automation of the distributed control system operation in three ways:

1) **Condition Assessment:** Assesses the condition of the equipment automatically to reduce human inspection tasks and unnecessary maintenance that occurs in a traditional periodic maintenance scheme. System assessment also provides valuable real-time decision support data for operational planning.
2) **Prognostics:** Predicts the onset of machinery failure to allow the command structure to match the use of the ship's machinery to the mission plan, or to enhance maintenance support. Prognostic capability expands support options and allows for cost effective planning and management.
3) **Automated Logistics:** Allows advanced scheduling and coordination of maintenance actions. Advanced triggering of logistics support events improves system availability and resource utilization.

Condition Assessment has two corollary functions:

1) To continuously monitor and estimate machine condition as the machine degrades with use and eventually degrades beyond designed engineering limits.
2) To identify unreliable or failed machine elements.

The ultimate CBM objective is to determine the overall health of the system and to provide a comprehensive assessment of diagnostic condition (hard failures), and prognostic condition (pending failures). Moreover, the CBM functionality supports the management of the system configuration as well as providing a capability to exercise the test/maintenance features of the subsystems. In order to identify both pending and actual failures, the CBM applications process the prognostics captured by the distributed control systems. The CBM applications compute performance indices such as "performance degradation" or "damage accumulation" based on known component analysis models/algorithms available for the plant equipment. It then compares the computed performance index to a mapping of "health phases" to determine if the component has transitioned to a different state of health or degradation. Depending upon the component and its health phase, an appropriate automated "action alert" (such as an indication to order a replacement part) may be triggered to facilitate resolution of this prognostic evaluation.

CBM Data Flow

It is envisioned that the CBM applications continuously monitor the ship equipment by analyzing data from CBM-specific sensors and data from the equipment control systems. Figure 2 illustrates the conceptual flow of data and the CBM analysis process. The process starts with sensor data collection at the process control level. The data is

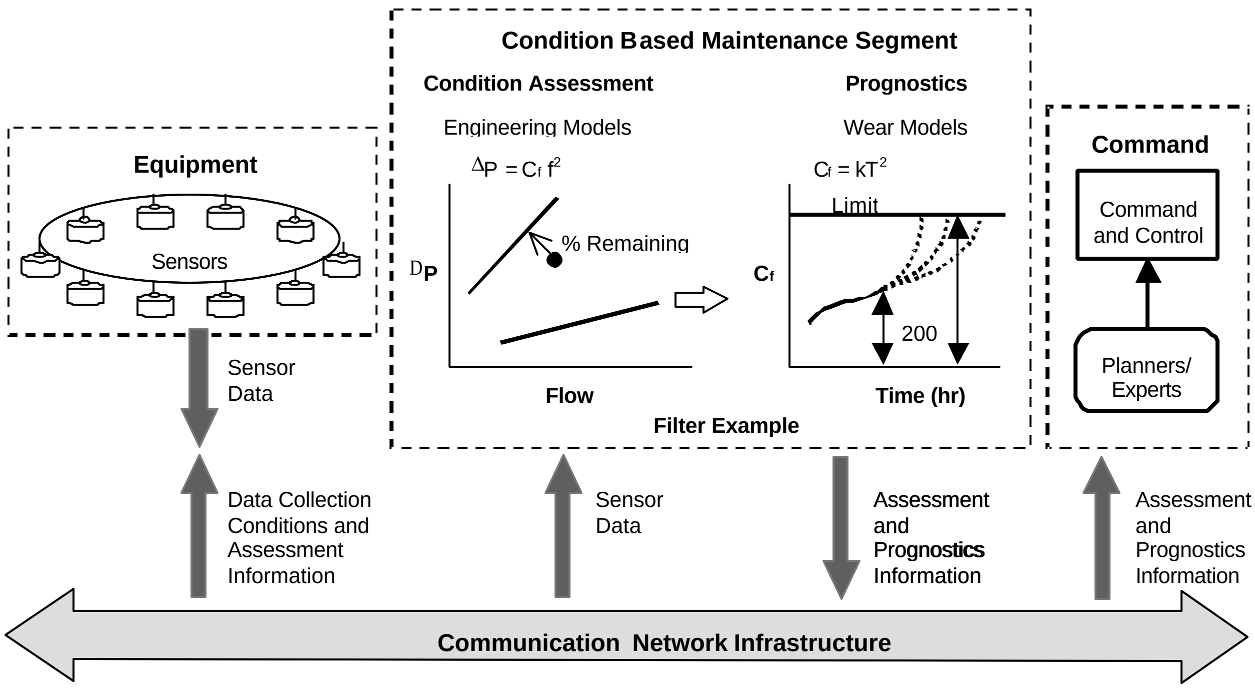

Figure 2: CBM Data Flows across the Ship Network Infrastructure

subsequently delivered to the CBM condition assessment algorithm for a particular machinery element. The condition assessment algorithm determines the condition of this element using a combination of engineering models that represent the process the element performs. This information is used as input for optimizing the ship's operation by determining which machines to operate. The prognostic algorithms use the condition assessment information to update or otherwise estimate the operating time available before a failure occurs. The prognostic information is then made available to the operators for further action. The ship's crew can then use the current and projected status to evaluate and update mission plans including maintenance activities.

CBM Technologies

Condition Assessment Technique: Many condition assessment software packages are available from commercial sources. Some of the assessment and prognostic algorithm tools have also been tested in both a naval and a commercial process environment. The DEI Group/IDAX has developed several tools that provide condition assessment and prognostics capabilities fielded in both commercial and Navy applications. Their Integrated Condition Assessment System (ICAS) is installed on many Navy ships providing propulsion/electric plant condition assessment and troubleshooting support for the ship's engineering crew. Other companies and institutions such as VibroTek, SwanTech, NRL, and General Electric provide tools that add condition assessment capabilities.

Condition assessment tools provide both Boolean logic and "fuzzy logic" heuristic algorithms. These algorithms combine the observed symptoms into machinery assessment rules for each failure mode of a machine. The observed symptoms reflect the machine state and its physical process. In this scenario, sensors measure the dynamic states in the physical process and the rules determine the change of that state based on the matching of symptomatic parameters in the assessment rule. The assessment rule represents the condition of the machine whenever it is found and triggered.

The analysis engine is composed of calculation component, trend evaluator and an expert heuristic engine based on crisp and fuzzy Boolean logic. Each diagnostic "fault" (or pattern) is directly associated with a sub-component of the system and targets a particular failure mode for early-detection. Each failure mode will contain a "pattern" comprised of symptoms for the condition assessment system to use as the expert evaluator. Each symptom is directly related to calculations or trend slopes that are dependent on physical sensor scanned values.

Prognostics Technique: The premise supporting prognostics: If failure modes are identified through patterns, then rate-of-change over time (in machine operating hours) of the pattern defines the failure mode's evolution rate and character. When the evolution rate and character has been determined, then the residual operating time for the failure mode is extrapolated using the known character of the wear. The amount of certainty in the estimation, or the accuracy of the estimation, is dependent on the following:

1) The accuracy of the baseline model used to define the failure mode
2) The accuracy of sensor processing including the sensitivity of the sensor, the accuracy in the data collection process, and its stability over time
4) The actual number of measured machine parameters and whether these machine parameters fully sense the conditions affecting wear of the machine
5) The accuracy of associations, or wear models, linking measured machine parameters to the degradation process.

IV. Machinery Condition Monitoring

The fundamental concept behind condition based maintenance consists of evaluating the system machinery from many aspects and assessing its electrical and mechanical condition. Vibration response and dynamic performance characteristics are the two major indications of machinery condition. The DCS typically provides continuous monitoring of these two characteristics and in some cases periodic samples having greater detail/resolution. For example, machinery performance is constantly monitored with normal operating instruments. However, specific performance tests may be periodically conducted to compute operating points and the efficiency of individual machinery cases. The frequency of the performance tests is a function of the machinery services. Similarly the vibratory behavior of the equipment is continually monitored and protected by the control system. Other types of information such as lube oil analysis, winding insulation resistance analysis, thermography, and current analysis on electric machinery might be incorporated into the equipment condition monitoring program.

The majority of machinery mechanical problems occur in three categories: alignment, balance, and incorrect clearances. These problems symptoms can generally be diagnosed using sensed data such as temperature, pressure, vibration and dynamic response. For example, data such as vibration, temperature and lubricant condition indicate some malfunctions within the machine under question that tend to show up as poor dynamic performance.

Distributed Control System (DCS) Characteristics

In addition to having the usual control logic, modern DCS's have the following features

- High-speed data collection and signal conditioning: Many signal input/output modules within the DCS have on-board processors that independently handle the numerical calculations.
- Vibration analysis algorithms: Vibration signal analysis that makes use of different computational strategies such as Fast Fourier Transform (FFT), Neural Nets (NN), and Wavelet.
- Dynamics identification algorithms: These are methods to estimate the on-line dynamic operational parameters of the equipment.

These features are available in many commercial DCS and also in some smart sensors and actuators.

The implementation of the analysis techniques in the DCS is similar to the CBM methodology aforementioned. The methodology is based on having a reference (known) model of the equipment characteristics and operation. The DCS continually measures and compares actual equipment data/performance to the expected output of the model. It assesses the equipment condition by analyzing the deviation of the expected results.

Vibration Response Monitoring

It has been known for many years that the mechanical integrity of a machine can be evaluated by detailed analysis of the vibratory motion[4]. Many mechanical problems are initially recognized by a change in machinery vibration amplitudes. In addition, the frequency of vibration, plus the location and direction of the vibratory motion are indicators of problem type and severity. Vibration characteristics can be distinctively divided into two types: forced vibration and free vibration. Typical forced vibration relates to problems such as mass unbalance, misalignment, and excitation of electrical or mechanical nature. Free vibration is a self-excited phenomenon that is dependent on the geometry, mass, and damping of the system, and typically caused by structural, acoustic resonance, and by aerodynamic or hydrodynamic excitation.

Vibration signals carry information about exciting forces and the structural path through which they propagate to vibration transducers. A machine generates vibrations of specific ‘color’ when in a healthy state and the degradation of a component within it my result in a change in the character of the vibration signals.[18] The overall vibration signal is a mixture of a host of components at different frequencies. These frequencies are primarily a function of the dimensions of the machine elements and their operating speeds, and the structural path along which the vibration signals propagate. A large variety of machinery possesses intrinsic dynamic characteristics that can provide a signature indicating their state of health. The state of health for the most part can be measured and analyzed in terms of the vibration signals.

Advanced distributed control systems include digital processing techniques to analyze the equipment vibration signals in both time-domain and frequency-domain. Time domain information is useful to detect short duration features and frequency domain data is necessary for tracking multiple frequency components that shift in time. The implementation of the signal processing algorithms can be done using different computation techniques. These techniques include but are not limited to Fast Fourier Transform (FFT), Neural Network, and Wavelet analyses which have been applied to vibration monitor and detection in gas turbine control systems.[8] Figure 3 illustrates the process of analyzing a time-based vibration signal data using Fourier technique. The result is a frequency spectrum which indicates the magnitude of the vibration at discrete frequency ranges. The control system can then utilize this information to determine if there has been a change in machinery characteristics and whether the change is acceptable for continued operation.

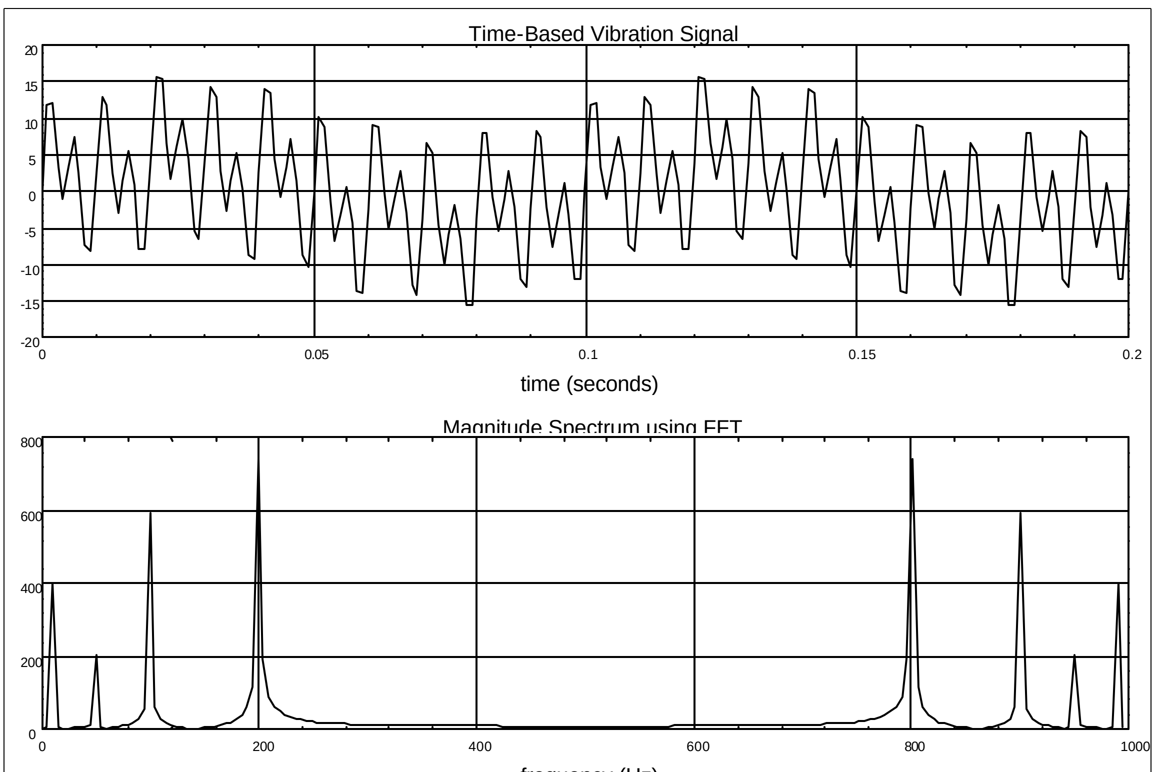

Figure 3: Fourier Analysis of Vibration Data

<u>Dynamic Performance Monitoring</u>

The dynamic response of the equipment is a good measure of its operational performance. Dynamic behavior of a system can usually be measured in two ways: step response and frequency response. To measure the step response, for example, the control system generates an excitation signal (step) to a selected piece of equipment. The appropriate equipment parameters are then measured and stored for a predetermined time frame. The analysis step involves contructing the time response of the parameters and comparing them it against a known response of the system.   The known response may be derived from mathematical models of the equipment in combination with engineering experience.

Figure 4 illustrates a step response analysis where the equipment is perturbed by a step input signal generated by the control system. The output of the system is measured and compared with that of a predefined model for the same input signal. Variations between the actual and the model (expected) output are analyzed to determine the possible performance degradation. For frequency response analysis, a similar process to the step response is performed, but now the input excitation signal is a sinusoidal signal having different frequency components. The system performance is then analyzed in terms of the frequency spectrum.

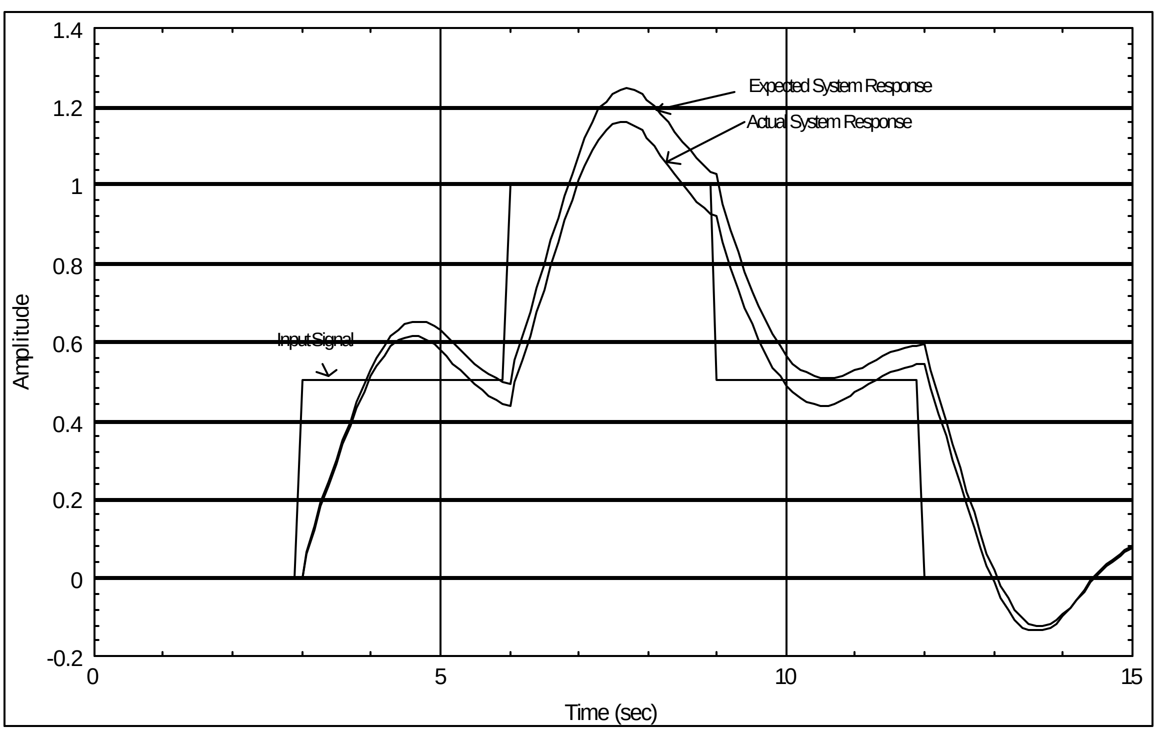

Figure 4: Condition Assessment Based on Step Response

This has been a brief discussion of the dynamic performance monitoring and analysis, also known as system identification techniques. The actual design and implementation of these techniques are relatively complicated in terms of formulating proper excitation level and frequency. The signal input amplitude and frequency are normally designed to match the frequency bandwidth of the selected equipment so that maximum information can be extracted out of the response data. These techniques are normally used to obtain the dynamic response of the equipment in order to design control system parameters. However, it can also be used effectively in assessing the deterioration of equipment performance due to mechanical or electrical problems in system or components.

V. Applications

The techniques of vibration and dynamic performance analysis described in the preceding section have been implemented in control systems for different applications. Other techniques and applications are being developed to improve system performance and reliability to support total CBM concept. All of these methods can be easily incorporated in a Distributed Control System and some of them are presented below.

Gas Turbine Condition Monitoring

There has been significant development in the area of gas turbine condition monitoring products. Some notable effort is by General Electric and Lockheed Martin Corporations who use control system information to perform gas-turbine condition monitoring. Intelligent Applications Ltd. developed Tiger, a gas turbine condition monitoring system, that has proven to reduce maintenance cost and improve operational performance.[16] This system utilizes turbine control system information to perform conditioning monitoring and analysis. During on-line operation, Tiger performs a variety of checks, including design limits, dynamic response and, consistency with model-based prediction.

Condition-Based Maintenance of Electrical Machines

Various efforts in industry have focused on the on-line monitoring of electrical equipment such as electrical motors and transformers. In many of these instances, local control systems collect data using advanced sensor technology and analyze them for equipment malfunction. This is primarily a part of the predictive maintenance development to detect electrical deterioration of equipment insulation system. For some components such as an electrical transformer, the condition of winding insulation has a major effect on long–duration outage[10]. The objective is to improve personnel safety and the application of on-line monitoring for incipient failures.

Many manufacturers provide motor controllers integrated with motors for variable speed motor operation. The integrated motor provides a compact package for distributed control enabling the machine to continuously monitor its own health. The built-in algorithmic techniques establish whether the motor's operating parameters such as vibration, current and temperature are within prescribed limits.

VI. Conclusion

Distributed control system suppliers are continually working to provide more predictive maintenance (condition monitoring) features and to help the system users put a host of other information from the automation environment to good use. The advent of smart sensors and actuators capable of communicating through system networks make use of a tremendous amount of available reliability data for CBM utilization. As computing power becomes less expensive and can be economically distributed to the equipment level control systems, more analysis can be executed in parallel with the process control routines. The overall goal is to analyze the change in the equipment condition, predict potential failures, and proactively implement (through a CBM infrastructure) maintenance. Cost of CBM implementation can potentially be reduced by distributing the CBM functions to lower level equipment DCS.

As the process control systems take on additional responsibilities in the areas of condition assessment, it will be necessary to develop better and more robust computational techniques to improve the efficiency and accuracy of data processing. Development in areas such as sensor data fusion, feature extraction, classification, and prediction algorithms are essential to determine the remaining useful life of a piece of machinery.

VII. References

1. Barkova, Natalia A., "The Current State of Vibroacoustical Machine Diagnosis", VibroAcoustical Systems and Technologies (VAST, Inc.), St. Petersburg, Russia.
2. Coleman, Neil and Coleman, R.E., "Dynamic Defect Detection", Sensor Magazine, August 1999, pp. 14-24.
3. Discenzo, Fred M., et. al, "Self-Diagnosing Intelligent Motors: A Key Enabler for Next Generation Manufacturing Systems", IEE Publication, London UK.
4. Eisenmann, Robert C. Sr., Eisenmann, Robert C. Jr., Machinery Malfunction Diagnosis and Correction, Prentice Hall, 1998.
5. Engel, Stephan J., et al., "Prognostics, The Real Issues Involved with Predicting Life Remaining", IEEE Publication 0-7803-5846-5/00, 2000, pp. 457-469.
6. Gonzalez, A. J., et al., Monitoring and Diagnosis of Turbine-Driven Generators, Electric Power Research Institute (EPRI), Published by Prentice Hall, 1995.

7. Hadden, George D., et al., "Shipboard Machinery Diagnostic and Prognostics/Condition Based Maintenance: A Progress Report", IEEE Publication 0-7803-5846-5/00, 2000, pp.277-292.
8. Harrison, Gregory A., Lockheed Martin Information Systems, Orlando Florida, personal communication.
9. Hess, Stephan M., et al., "An Evaluation Method for Application of Condition-Based Maintenance Technologies", 2001 Proceedings Annual Reliability and Maintainability Symposium", pp. 240-245.
10. Kohler, J.L., et. al., "Condition-Based maintenance of Electrical Machines", IEEE Publication 0-7803-5589-X/99, 1999, pp. 205-211.
11. Nguyen, T.V., Lockheed Martin Information Systems, Orlando Florida.
12. Reichard, Karl M., et al., "Application of Sensor Fusion and Signal Classification Techniques in a Distributed machinery Condition Monitoring System", Sensor Fusion: Architectures, Algorithms, and Applications IV, Proceedings of SPIE, Vol. 4051, 2000, pp. 329-336.
13. Schulz, Glenn, "Integrating Information to Achieve Plant-wide Asset Health", Control Solutions magazine, March 2001, pp. 36-40.
14. Starr, A.G., "A Structured Approach to the Selection of Condition Based Maintenance", 5th International Conference on FACTORY 2000, April 2-4 1997, Conference Publication No. 435, IEE 1997, pp. 131-138.
15. Tenbohlen S., "Monitoring of Power Transformers through Field Bus and Process Control Engineering".
16. Travé-Massuyè, Louise, Milne, Robert, "Gas-Turbine Condition Monitoring Using Qualitative Model-Based Diagnosis", IEEE Expert, May-June 1997, pp. 22-31.
17. Werzer, J.M., et. al., "Diagnostic and Condition Assessment Techniques for Condition Based Maintenance", 2000 Conference on Electrical Insulation and Dielectric Phenomena, pp. 47-51.
18. Williams, J.H., et al., Condition-Based Maintenance and Machine Diagnostics, Chapman & Hall, 1994.